Journal of Criminal Justice 68 (2020) 101685

Contents lists available at ScienceDirect

Journal of Criminal Justice

journal homepage: www.elsevier.com/locate/jcrimjus

Crime and income trajectories preceding lethal and non-lethal violence

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ARTICLE INFO

Keywords:
Violence
Homicide
Trajectory
Criminal history
Social disadvantage

ABSTRACT

Purpose: This study analyzes the pathways leading to violent offending. We examine whether the lethality of a violent crime could be predicted based on individuals' prior history of violent crime and income, and whether the trajectories of lethal offenders are distinguishable from the pathways of non-lethal offenders.
Methods: We use a sample of police-reported violent crimes committed in Finland in 2010–2011 (N = 26,303) and contrast the pathways to homicide with the trajectories leading to petty assault, assault, aggravated assault, and attempted homicide. Group-based trajectory modeling is applied for identifying individuals with similar trajectories, and multilevel modeling is used for estimating the mean trajectories for offenders of differing severity.
Results: Results indicate that homicide offenders display a clear escalation in the frequency of violent offending and a slight decrease in income prior to the offense, but the pathways to homicide largely resemble the pathways to aggravated assault and attempted homicide.
Conclusions: The lethality of violent offending cannot be predicted from the offender's crime and income. The greatest divide in the violence severity continuum is between offenders of assaults and offenders of aggravated assaults, with the latter group largely resembling offenders of completed and attempted homicides.

1. Introduction

Homicide is the most serious form of interpersonal violence and generally regarded as an extreme manifestation of various risk factors. Yet lethal violence tends to occur in similar contexts as non-lethal violence: violence often originates from the escalation of trivial disputes (Felson, 2017; Griffiths, Yule, & Gartner, 2011), and on many occasions, the lethality of an incident can depend on chance. Moreover, sometimes the roles of homicide offender or homicide victim are determined only after the end of the violent conflict (Loeber, Lacourse, & Homish, 2005, p. 203; Luckenbill, 1977). For instance, in a review of studies investigating this victim-offender overlap, Jennings, Piquero, and Reingle (2012) reported consistent evidence for a substantial overlap among offenders and victims of violent crime.

Lethal offenders are reported to have a history of prior crimes and experience various forms of social disadvantage (e.g., Farrington, Loeber, & Berg, 2012), but it is not known whether the criminal careers or social disadvantage of lethal offenders tend to *escalate* before a lethal incident occurs, and whether homicide represents a culmination of an individual's criminal career. Sampson and Laub (1997, 2003) describe, in their life-course theory of crime, a process of cumulative disadvantage. This notion suggests that crime causes “a series of negative pushes” (DiPrete & Eirich, 2006, p. 291) or a “snowball effect” that increases the risk of later offending (Sampson & Laub, 1997, p. 15). According to this perspective, adverse life events such as a divorce, job loss, or violent crime victimization could push an individual into a downward spiral or accelerate one's negative trajectory of criminal behavior, leading to more severe violence. This formulation comes close to Moffitt's (1993, p. 684) description of harmful “snares” such as teenage parenthood, patchy work histories, or time spent in prison, which narrow the options for conventional behavior and can therefore strengthen the continuity of antisocial behavior. There are also notable similarities to Agnew's (1992) concept of “general strain”, which refers to multiple negatively perceived events and conditions that tend to have *a cumulative impact* on criminal behavior. General strain theory makes a distinction between objective and subjective strain and thus emphasizes the importance of individuals' subjective evaluations of their conditions (Agnew, 2001). With respect to the subjective nature of strain, Agnew and Messner (2015) focus on the personal assessments individuals make of their own standing. They state that when certain threshold levels are reached, these assessments have a *nonlinear* effect on the “frequency, seriousness, and duration of offending” (Agnew & Messner, 2015, p. 588). Therefore, the effect of the accumulation of various risk factors may not be straightforward.

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https://doi.org/10.1016/j.jcrimjus.2020.101685
Received 21 January 2020; Received in revised form 15 April 2020; Accepted 15 April 2020
Available online 01 May 2020
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To summarize, an array of theories links criminal history and social disadvantage to increased offending, but there is little research on whether these trajectories of crime and social disadvantage can explain the escalation of violence and whether lethal offenders can be distinguished from non-lethal offenders before they commit lethal violence. Since the criminal sanctions are usually determined by the outcome of a violent encounter, these questions are highly salient for criminal policies. Yet they are equally relevant for criminological theories explaining lethal violence in general.

This study aims to fill this gap in the literature by investigating whether the years preceding homicide are characterized by a spiral of increasing crime and decreasing income, and whether the trajectories of lethal offenders are distinguishable from the pathways of non-lethal offenders. We draw from a nationally representative sample of police-reported violent crimes of differing severity committed in Finland in 2010–2011 (N = 26,303) and use two separate approaches to examine the distinctiveness of violent crime and income trajectories preceding homicide (n = 203) versus other forms of violence, such as attempted homicide (n = 318), aggravated assault (n = 1995), assault (n = 15,817), and petty assault (n = 7970). These violent offenses of differing severity are used as index offenses, and we analyze the years preceding these crimes. First, we apply group-based trajectory modeling which identifies groups of individuals who appear similar on the basis of these trajectories, and then examine how group membership differs by the severity of the offender's index offense. Effectively, here we are asking the *predictive question:* is knowledge of preceding crime and income trajectories useful in predicting the seriousness of a violent offense that follows? The second approach, multilevel modeling, estimates the mean trajectories by index offense to see how these groups differ on average. In other words, here we examine the mean trajectories of crime and income conditional on the index offense.

2. Prior research

The behavioral continuity and discontinuity of criminal offending is a central notion of the criminal career paradigm (Piquero, Farrington, & Blumstein, 2003; Sullivan & Piquero, 2016). Studies on criminal careers have focused, for example, on specialization, escalation, and desistance (DeLisi & Piquero, 2011). Recent research by DeLisi, Ruelas, and Kruse (2019) demonstrated continuity in lethal offending: prior murder conviction was associated with subsequent homicide offending. On the other hand, a study by Broadhurst, Maller, Maller, and Bouhours (2018) reported that, due to the rarity of homicide offending, only a small proportion of homicide offenders committed a new lethal incident, but other serious offenses were relatively common. Indeed, prior studies have reported that lethal offenders do not seem to specialize in lethal offending, but tend to have diverse criminal histories (Farrington et al., 2012; Ganpat, Liem, Van der Leun, & Nieuwbeerta, 2014; Suonpää, Kivivuori, & Aaltonen, 2018).

Studies on escalation have yielded somewhat mixed results. Blumstein, Cohen, Das, and Moitra (1988) analyzed arrest histories of American adults and reported some support for escalation in crime seriousness after aggravated assaults for white offenders, but similar patterns were not found among black offenders. Liu, Francis, and Soothill (2011) followed a birth cohort from England and Wales and suggested that ageing of the offenders was associated with de-escalation through maturation, but the increase in number of conviction occasions was linked with the escalation in crime seriousness. More recently, a study based on the same data identified three distinct latent groups of offenders: The largest group showed a pattern of escalation in crime seriousness when the number of conviction occasions increased, and de-escalation with increasing age, whereas the other two groups displayed non-linear effects with age and non-significant effects of convictions (Francis & Liu, 2015). In contrast, in their study on escalation of seriousness of inmate misconduct in US prisons, Cihan, Sorensen, and Chism (2017) reported that only a relatively small proportion of prisoners showed a pattern of committing more severe offenses over time. A Canadian study by Cale, Plecas, Cohen, and Fortier (2010) approached the question on escalating in violence by comparing single-time homicide offenders with repeated homicide offenders. Consistent with the theory of cumulative disadvantage, the repeated homicide offenders appeared to be a more disadvantaged group: they lacked employment and experienced escalating substance abuse and reduction in their social support more often than single-time homicide offenders.

The question of escalation is especially relevant for studies aiming at predicting lethal offending based on individuals' prior criminal histories. Yet, homicide research has often developed separately from other studies on violent behavior (Kivivuori, 2017). Homicide is a relatively rare incident and the number of lethal offenders is therefore low in most longitudinal datasets. Hence, it is not surprising that only a handful of studies have examined to what extent homicide offenders resemble offenders of other forms of violence, and to what extent they appear as a group with distinct characteristics.

Loeber, Pardini, et al., 2005 used longitudinal data from the Pittsburgh Youth Study (PYS) for examining whether the homicide offenders could be distinguished from other violent offenders based on different risk factors. They reported several important predictors of lethal violence, but also a high rate of false positives since a high proportion of youths with multiple risk factors did not commit homicide. Moreover, Farrington et al. (2012) analyzed the newer sample from the PYS and reported a dose–response relationship between various early-life risk factors and probability of lethal offending: the higher the risk score, the higher the probability of becoming a homicide offender. Similar to studies on earlier samples from the PYS, they too reported a high rate of false positives (the newer PYS dataset included less than 40 homicide offenders). Smit, Bijleveld, Brouwers, Loeber, and Nieuwbeerta (2003) used administrative data from the Netherlands and did not report statistically significant differences between the criminal histories of offenders of completed and attempted homicides. More recently, Suonpää et al. (2018) reached similar conclusions by analyzing official records from Finland. In contrast, Ganpat et al. (2014) analyzed Dutch data on crime records and stated that non-lethally violent perpetrators had a more severe criminal history than lethally violent offenders – however their results were sensitive to how the criminal history was measured. Interestingly, DiCataldo and Everett (2008), who compared young American males committing lethal and non-lethal violence, also reported that non-lethal offenders had a more severe criminal history and more problematic backgrounds. Yet, they warned that some of the differences identified in the study may have been caused by selection bias since offenders who had not committed homicide needed to manifest a high rate of risk factors to end up in the secure detention program where the data were collected from. Similarly, Dobash, Dobash, Cavanagh, and Medina-Ariza (2007), who compared lethal and non-lethal violence against intimate female partners using British data, discovered that homicide offenders were less likely to have had at least one previous conviction, and had more conventional backgrounds and employment situation than non-lethally violent men.

The studies described above used chi-square test (DiCataldo & Everett, 2008), nonparametric Kruskal-Wallis test (Smit et al., 2003), or multivariate statistics such as logistic regression (Dobash et al., 2007; Ganpat et al., 2014; Loeber, Pardini, et al., 2005; Suonpää et al., 2018) for examining whether homicide offenders differed from non-lethal offenders. A prominent method for analyzing crime trajectories has been group-based trajectory modeling (GBTM, or latent class growth analysis LCGA), which was first introduced by Nagin and Land (1993). GBTM has its origins in a criminal career paradigm, and has been applied widely in analyzing the relationship of age and criminal offending (Nagin, 2016; Nagin & Odgers, 2010). It is a useful technique for data reduction for descriptive purposes or summarizing previous behavior when studying future development (Skardhamar, 2010). For instance, Tahamont, Yan, Bushway, and Liu (2015) applied GBTM for analyzing the trajectories of first-time prisoners in the USA and reported that even though a substantial portion of the first-time prisoners were heavily involved in the criminal justice system years before their first incarceration, almost a quarter of the individuals sentenced to prison were unknown to the criminal justice system prior to the arrest resulting in their incarceration.

Despite multiple studies exploiting GBTM, the methodology has rarely been applied for contrasting the developmental trajectories of lethal and non-lethal offenders. In his review of more than 80 criminological studies using trajectory analysis between 1993 and 2003, Piquero (2008, p. 40) stated that due to the small number of studies using offender-based samples "little information is known about the factors that relate to trajectory differences within serious offenders followed into adulthood". An exception is a study using the data from the aforementioned PYS, in which Loeber, Lacourse, and Homish (2005) applied GBTM for examining whether lethal offenders were assigned to the highest and most stable trajectory of violent individuals. They reported that the two highest trajectories of violence seriousness accounted for roughly fourth-fifths of the homicide offenders (81.8%) and roughly three-fifths of non-lethal violent offenders (61.7%).

Aside from the research focusing on the criminal histories of offenders, the role of different forms of strain and disadvantage have been analyzed. Nordic register data in particular have been fruitful for research focusing on the timing of different life-events and within-individual change over the life-course (for a review of Nordic register data, see Lyngstad & Skardhamar, 2011). For instance, a Finnish study analyzing the within-individual association between economic problems and violent offending indicated that changes in employment status were not associated with changes in violent offending (Aaltonen, Macdonald, Martikainen, & Kivivuori, 2013), but experiencing debt problems seemed to slightly increase violent offending in the months following (Aaltonen, Oksanen, & Kivivuori, 2016). Moreover, a population-based study from Sweden found evidence that various stressful events such as exposure to violence or loss of parents were associated with increased violent offending in the week following the exposure (Sariaslan, Lichtenstein, Larsson, & Fazel, 2016), and a Finnish study reported evidence of a state-dependent effect of offending on subsequent victimization (Aaltonen, Kivivuori, & Kuitunen, 2018). To summarize, prior studies have shown that increased violent offending is associated with cumulative disadvantage such as economic problems or stressful life-events, but to date there is no empirical evidence that lethal offenders experience *more* cumulative disadvantage than severe non-lethal offenders.

Overall, existing research studying the pathways leading to violent offending have identified various risk factors such as criminal history, economic problems and stressful life-events, but comparisons between lethal and non-lethal offenders have been rare. Furthermore, the majority of the studies explicitly comparing lethal and non-lethal offenders have not exploited more advanced methods capable of identifying distinct groups or modeling the dynamic nature of crime and income histories of the offenders, and they have often suffered from small sample sizes.

3. Current study

The purpose of the current study is to analyze the pathways leading to violent offending. In particular, we examine whether the years preceding homicide are characterized by a downward spiral of escalating criminal offending and decreasing income, and whether such trajectories among lethal offenders are distinct from non-lethal offenders. The methodology used in this paper is twofold: First, we use group-based trajectory modeling (GBTM) for identifying individuals with similar trajectories and assigning them to latent groups, and then we test whether group membership is associated with the severity of the index offense. Second, we use multilevel modeling and predict the mean crime and income trajectories separately by each type of index offense.

We add to prior research by using a large dataset comprising multiple measurement points from the years preceding the index offense, and by applying advanced statistical methods suitable for capturing the differences and similarities of the pathways leading to violent crimes. The unique register data resources available in Finland provide a dataset with only a few or no non-responses or attrition, and the use of personal identification numbers allows for linking the dataset with other administrative data sources containing information on an individual's criminal history and taxable income.

4. Data and methods

4.1. Data

Our dataset draws on police-reported violent crimes of differing severity: a total population sample of homicide suspects during 2010–2011, and a 50% random sample of suspects of selected, non-lethal violent crimes from the same timeframe. The dataset was initially collected in the research project Risk Factors of Crime in Finland (RFCF) by the Institute of Criminology and Legal Policy, and consisted of individuals investigated by the police as suspects, regardless of whether the criminal investigation led to conviction, or whether the rubric changed in court. According to Sellin's law, criminal statistics generated closer to the actual event provide more reliable information on the number and characteristics of violent crimes than statistics formed later in the criminal process (Sellin, 1931). Regarding non-lethally violent crimes in particular, non-prosecution is relatively common (Lappi-Seppälä, Niemi, & Hinkkanen, 2015). Thus, since our objective is to analyze committed violence instead of sentencing practices, we find police statistics more suitable. For simplicity, suspects are referred to as offenders in this study.

Assault offenses included in the sample were *petty assault, assault*, and *aggravated assault*, and the class of homicide consisted of the penal code titles of *manslaughter*, *murder, killing*, or *infanticide*[1]. Prior research has shown that in Finland, a majority of homicides result from drunken quarrels between acquaintances, family members, or friends (Liem et al., 2013; Savolainen, Lehti, & Kivivuori, 2008) and only one-fifth of homicides (19%) are reported to include premeditation (Lehti, Suonpää, & Kivivuori, 2017). Attempted homicide refers to an attempt to commit any of these four lethal offenses, and it is a punishable act. Suspects of *negligent homicide* and *grossly negligent homicide* were included as homicide offenses when these offenses were committed in conjunction with the penal code titles on assault crimes.[2]

As reported in an array of studies on criminal behavior (e.g., Elonheimo et al., 2014; Falk et al., 2014; Martinez, Lee, Eck, & O, 2017), a small number of offenders commits the majority of crimes. This is also the case in our dataset: the same individuals were suspected of various crimes during the same timeframe. In each category, the index offense was the first offense committed by the individual, and the later crimes of the same category committed by the same individual were omitted from the dataset. Hence, the same individual could be counted five times in the whole dataset, once in each of the violent crime types. Since the minimum age of criminal liability is 15 years in Finland, offenders under 15 years old were omitted from the data. After these data preparations, the offenders were assigned an individual ID number and treated as different observational units.

Our final dataset consisted of offenders of five different index offenses: petty assault ($n = 7970$ offenders), assault and attempt

[1] Sanction for manslaughter is imprisonment for a fixed period of at least 8 years, sanction for murder is life imprisonment, sanction for killing is imprisonment for 1–10 years, and sanction for infanticide is imprisonment for at least 4 months and at most 4 years (Finnish penal code 21: 1–4 §).

[2] Sanction for negligent homicide is a fine or imprisonment for at most 2 years, and sanction for grossly negligent homicide is imprisonment between 4 months and 6 years (Finnish penal code 21: 8–9 §).

(n = 15,817), aggravated assault and attempt (n = 1995), attempted homicide (n = 318), and completed homicide (n = 203). The Finnish personal identification number was used for linking the individual with other data sources: Basic demographic data, such as gender, age, and immigrant background, were acquired from the Population Register Centre. Taxable earned income including state benefits for the 5 years preceding the index offense (annual income, henceforth) was obtained from the Finnish Tax Administration, and inflation-adjusted for the year 2010 level. If the information regarding taxable income was not found from the registers, we interpreted that the individual had not received taxable income during the measurement period. Information regarding the police-reported violent crimes, all criminal convictions, and prior incarcerations was available for 9 years preceding the index offense: the data on police-reported violent crimes and convictions were gathered from the police, and the number of days spent in prison was acquired from the National Prisoner Database. Since the data were gathered from Finnish registers only, they are likely to be less reliable considering newly arrived immigrants. Yet, this kind of missingness would be unlikely to cause bias for comparison between groups since immigrant status was taken into account in all of the models.

4.2. Methods

4.2.1. Matching

For estimating the latent trajectories of crime and income preceding the index offense, we used GBTM. Before fitting the model, we applied a matching procedure using genetic matching algorithm implemented in the R package *Matching* for controlling the substantial differences in the demographic structures between the groups of offenders of differing severity ("Full Sample" in Appendix). By balancing individual covariates rather than a single propensity score, the automated iterative algorithm finds the set of matches which minimize the discrepancy between the distribution of observed confounders in the treated (homicide offenders) and control groups (non-lethal offenders), leading to a sample where the covariate balance is maximized (Sekhon, 2011). In addition to gender and age, which are well-known correlates of violent behavior, immigrant background is also reported to be associated with increased criminal offending in the Nordic countries (Martens & Holmberg, 2005; Skardhamar, Aaltonen, & Lehti, 2014). Therefore, matching was done based on three demographic variables: offender's gender (male/female), age (at the time of the index offense), and immigrant background (born in Finland/not born in Finland or not known).

We used homicide offenders (n = 203) as a control group and looked for suitable matches without replacement from each of four groups (three matches for each homicide offender from the offenders of petty assault, assault, and aggravated assault, and one match for each homicide offender from the offenders of attempted homicide), leading to a matched sample of 2233 individuals. As shown in Appendix ("Matched Sample"), a good balance of demographic variables between groups of different types of crime was reached. This way the subsequent analysis of the association between severity of crime and latent group membership is not caused by differences regarding gender, age and immigrant background, because the five groups are equal on these measures.

4.2.2. Group-based trajectory modeling (GBTM)

GBTM is a specialized application of finite mixture modeling designed to identify the groups of individuals following similar developmental trajectories (Jones & Nagin, 2013). We used the matched sample and fitted two separate models for crime and income trajectories looking backward from the index offense. The analyses were conducted using Stata package *Traj* (Jones & Nagin, 2013). The model's estimated parameters are the product of maximum likelihood estimation, and the individual differences in trajectories are summarized by finite sets of different polynomial functions of time which account for a latent trajectory group (Nagin, 2005). A polynomial relationship is used to model the link between time before the index offense and behavior preceding the crime. For crime trajectories, we used semiannual intervals (6 months), resulting in 18 measurement points across the 9 years preceding the index offense. The outcome variable was a dichotomous variable indicating whether the individual had been arrested for violent crime (1 = yes, 0 = no) during any time in the given 6-month period. Since the outcome variable was dichotomous, we used a logit model and allowed for linear, quadratic and cubic functions of time (Jones & Nagin, 2013; Nagin, 2005). Considering the income trajectory, we had annual data from the 5-year period preceding the index offense, leading to five measurement points. The dependent variable was the average annual income within the time period. We fitted a linear model and used linear, quadratic and cubic functions of time (Jones & Nagin, 2013; Nagin, 2005).

The choice of the number of trajectory groups should be made so as to achieve an optimal approximation for the distribution of the outcome variable in a heterogeneous population. For selecting the optimal number of latent groups, we used the criteria suggested by Nagin (2005) and thus examined Bayesian information criterion (BIC), Akaike Information Criterion (AIC), the average posterior probability of group assignments (AvePP), and the odds of correct classifications (OCC). Both BIC and AIC increase when the goodness-of-fit improves, but BIC tends to favor more parsimonious models (Brame, Nagin, & Wasserman, 2006; Nagin, 2005). Nagin (2005: 88, 89) suggests the rules of thumb that an adequate model has the AvePP of each group at least 0.70, and the OCC of each group greater than 5.0.

In cases where goodness-of-fit statistics are not capable of selecting an optimal model, Nagin (2005: 77) suggests considering the objectives of the analysis and finding a model that best captures the "distinctive features of the data in as parsimonious a fashion as possible". Hence, adding to prior criteria of choosing the best model, we avoided the solutions that would lead to groups with too few individuals and would thus violate the statistical assumptions of the subsequent chi-square test estimating the association of the latent trajectory and index offense (Bewick, Cheek, & Ball, 2004).

4.2.3. Multilevel random intercept model

For further examining the associations between severity of the index offense and violent offending history and annual income during the years preceding the crime, we adopted a regression framework. Since our dataset is a longitudinal design where we have repeated measures nested within persons, we applied multilevel modeling techniques (also known as hierarchical models) which take into account the dependency across time and explicitly models it (e.g., Gelman & Hill, 2007). Multilevel modeling identifies the average trend over time, quantifies the degree of variation around this average and assumes a specific error distribution (typically Gaussian) around the overall average (Sweeten, 2014).

Instead of the aforementioned matched data, we used the entire dataset with 26,303 offenders and fitted two separate two-level models for history of violent crime and income. In both of the models, the two levels consist of responses (level 1) within individuals (level 2). Individual-level intercepts were allowed to vary at the baseline, and different slopes were allowed for different types of crime by allowing an interaction between both time and time squared. The models were adjusted for the sociodemographic variables (gender, age, and immigrant background) used in the trajectory models. Considering the model with criminal history, we fitted a logistic random intercept model and used data from 9 years before the index offense, resulting in 18 semiannual measurement points. As in the trajectory model, the outcome variable was a dichotomous variable indicating whether the individual had been arrested for violent crime during the given 6-month period. Considering the model with annual income, we fitted a linear random intercept model using data from five annual measurement points. In both of the models, the reference category was assault

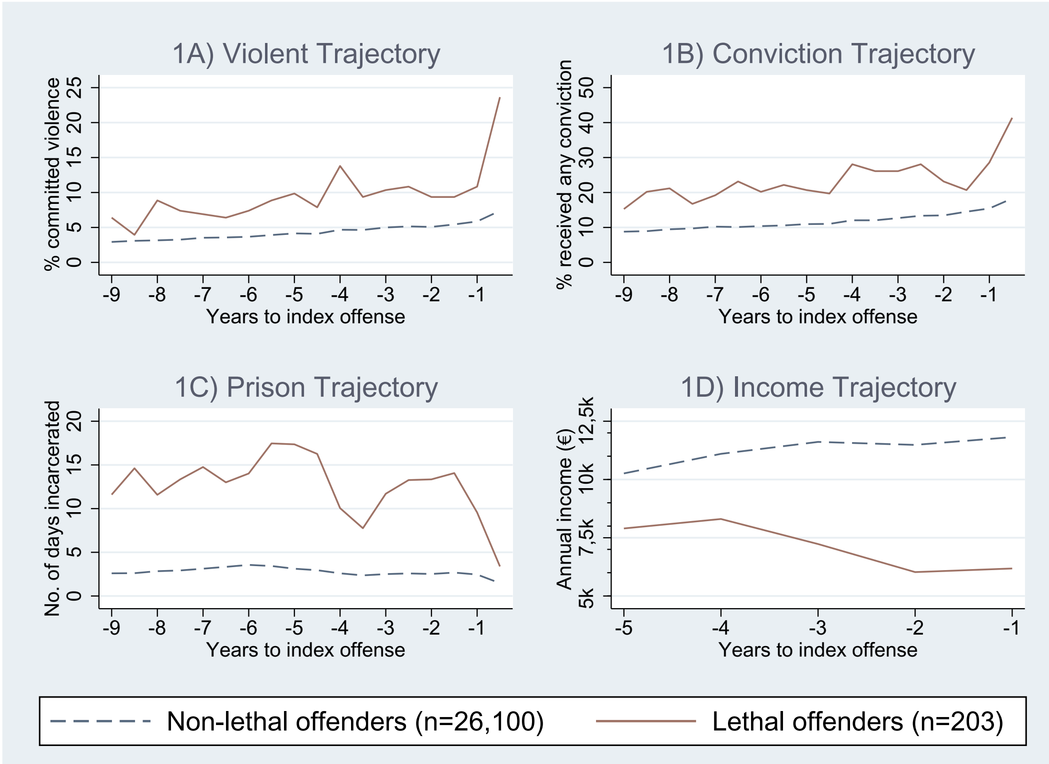

Fig. 1. Average violent crime, conviction, prison and income trajectories (N = 26,303).

offenders (n = 15,817), and the objective was to examine if more severe offenders – especially lethal offenders – had a more severe criminal history and experienced more economic disadvantage (measured by annual income) years preceding the index offense. To assist in the interpretation of the estimates, we report the predicted probabilities of outcome variables at each measurement point and fix the demographic covariates at their mean values. Multilevel models and GBTM were conducted by Stata 15.1 (StataCorp, College Station, TX).

5. Results

We first explored visually how the average violent crime (Fig. 1A), conviction (Fig. 1B), prison (Fig. 1C) and income trajectories (Fig. 1D) of homicide offenders (n = 203) and non-lethal offenders (n = 26,100) developed in the years preceding the index offense. The two groups exhibited substantial differences throughout the measurement periods, and the results display a pattern of escalation in quantity of criminal offending. More fluctuation was observed among homicide offenders, which is partly explained by the relatively small size of the group. For homicide offenders, the share of violent arrests increased from 6 to 24% during the observation period, whereas for the non-lethal offenders, the analogous proportion stayed between 3 and 7%. A similar pattern was observed regarding conviction trajectory, which is not restricted to violent offenses but refers to a wider scope of criminal activity. Regarding the evolution of the average number of days incarcerated each year, no escalation was observed. Rather, the average number of days spent incarcerated decreased as the index offense approached. Again, homicide offenders displayed substantial fluctuation, whereas the changes among non-lethal offenders were small.

Finally, offenders of non-lethal violence had distinctively higher annual incomes than homicide offenders (€10,261 versus €7899) already at the beginning of the 5-year study period, and the difference was greater 1 year before the index offense (€11,818 versus €6181). Yet, the average income of all groups was substantially lower than the national average income: in 2010 the mean of the monthly earnings of a full-time worker in the age group 35–39 was €3187, and the median was €2898 (Statistics of Finland, 2019) which makes the annual median income of that age group roughly €35,000. Thus, the results indicate that the majority of the individuals in the dataset were only sporadically employed during the years preceding the index offense. It should be noted that the standard deviations of days spent in prison and annual income were large, with distributions strongly skewed to the right. To conclude, a crude comparison between all non-lethal and lethal violent offenders indicated a substantial differences between the average violent crime, conviction, prison and income trajectories of the two groups.

5.1. Latent trajectories

5.1.1. Violent crime trajectories

As described in the Methods section, the goal of the GBTM is to identify the groups of individuals with distinctive individual-level trajectories. BIC suggested a four-group model, but the difference between the four-group (−8899.30) and three-group (−8906.90) model was small, whereas AIC suggested a six-group model, which would have led to small subgroups without meaningful interpretations (Table S1[3]). Examining the AvePPs, the threshold of 0.70 was achieved in the models with two, three, and four groups. Considering the OCC, the suggested threshold greater than 5.0 was obtained only in the two- and three-group estimation. Based on the combination of fit indices, we chose the three-group model, which was parsimonious and still capable of identifying different pathways. The resulting model parameters are displayed in Table S2.

The three-group model (Fig. 2) identified three qualitatively distinct trajectories: offenders with very low arrest probabilities during the first half of the follow-up period and then rising slowly (Trajectory 1: Rare violent offending, 72.7%), offenders whose arrest probabilities

[3] Tables S1-S6 are published in online supplementary material.

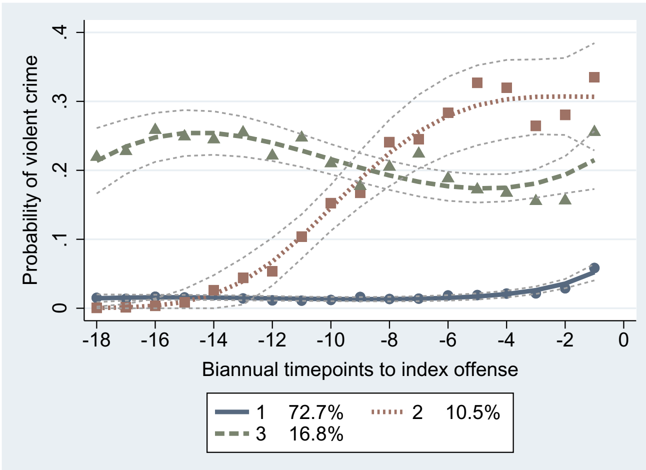

Fig. 2. Latent criminal trajectories of the offenders (N = 2233).

increased steeply during the follow-up period (Trajectory 2: Increasing violent offending, 10.5%), and offenders whose arrest probabilities were quite stable, around 20%, throughout the follow-up period (Trajectory 3: Persistent violent offending, 16.8%). Persistent violent offenders had also a distinctively higher starting level than the other two groups. The total number of violent crimes during the 9-year measurement period was substantially smaller among rare offenders (mean: 0.40; SD: 0.77) than increasing offenders (mean: 4.76; SD: 3.28) or persistent offenders (mean: 6.10; SD: 3.86). The individuals assigned to the trajectory of rare violent offending were, on average, a few years older, more often females, had substantially higher annual income and had spent fewer days incarcerated annually than offenders assigned to trajectories of increasing or persistent offending (Table S3).

Since the offenders of more severe index offenses had spent more days in prison on average (Appendix), we re-estimated the GBTM while taking into account the days served in prison. In analyses not reported here but available from the corresponding author, the indicator of violent crimes was coded as missing for each individual in each semi-annual measurement point in which the individual had stayed in prison more than half of the days (>91 days). The slopes were nearly similar but a slightly greater share of the individuals were assigned to Trajectory 1 (73.8%) and Trajectory 2 (13.3%), and, correspondingly, a slightly smaller share of the individuals to Trajectory 3 (13.0%). To summarize, the results indicated that the days spent in prison had only a small impact on the violent trajectories.

Next, we examined the association between the index offense and crime trajectory group membership. The results shown in Table 1 indicated that the type of index crime was significantly associated with criminal trajectory assignment (χ^2 = 116.44, p < .001). For instance, more than four-fifths of the petty assault offenders (84.4%) were assigned to the group of rare violent offending (Trajectory 1). For lethal offenders, the corresponding proportion was 59.1%. The trajectory of persistent violent offending (Trajectory 3) was the most common

Table 1
The associations between the index offense and criminal trajectory group (N = 2233).

	N	TRAJ 1	TRAJ 2	TRAJ 3	All
PA	609	84.4%	6.2%	9.4%	100.0%
A	609	80.3%	8.9%	10.8%	100.0%
AA	609	67.7%	11.5%	20.9%	100.0%
AH	203	59.6%	12.3%	28.1%	100.0%
CH	203	59.1%	19.7%	21.2%	100.0%

PA = Petty assault; A = Assault; AA = Aggravated assault; AH = Attempted homicide; CH = Completed homicide; p < .001; χ^2 = 116.4354.

among the offenders of attempted homicide: more than one-fourth of attempted homicide offenders (28.1%) and roughly one-fifth of offenders of completed homicide (21.2%) and aggravated assault (20.9%) were assigned to that group, compared to approximately one-tenth of petty assault offenders (9.4%) and assault offenders (10.8%). Attempted and completed homicide offenders largely resembled each other on their probability to be assigned to the trajectory of rare violent offending (59.6% and 59.1%, respectively), whereas the trajectory of persistent violent offending was more common among lethal offenders (28.1% vs. 21.2%). In pairwise comparisons not shown here but available from the corresponding author, lethal offenders differed statistically significantly at the 0.05 level from all index offense groups except attempted homicide offenders (χ^2 = 5.43, p = .07), who also differed from petty assault (χ^2 = 47.35, p < .001) and assault (χ^2 = 27.92, p < .001) offenders. To summarize, offenders with the more severe index crimes were, on average, more often assigned to the trajectories of increasing or persistent violent offending.

5.1.2. Income trajectories

For analyzing the socioeconomic disadvantage of the offenders during the years preceding the index offense, we estimated latent income trajectories for offenders. The values of BIC and AIC kept increasing when the number of groups increased, but when the number of groups surpassed three, the model suggested groups consisting of less than 0.5% of the individuals in the data, and after the six-group solution, we stopped adding new groups (Table S4). The AvePPs and OCCs surpassed the suggested thresholds in each of the models and were therefore not useful at separating the best model. We then examined the different pathways the models were suggesting. The shapes of the trajectories were essentially flat in each of the models: the differences between groups were caused by different levels rather than different slopes. None of the models were able to capture, for instance, decreasing income trajectories. We rejected the solutions with groups smaller than 1% of the individuals and chose the three-group model. The model parameters are shown in Table S5.

The three-group model (Fig. 3) identified three qualitatively distinct trajectories which differed mainly by the level of income. The majority of offenders were assigned to the trajectory of extremely low income (Trajectory 1: Lowest income, 68.2%), with a mean annual income of €4445 (SD: €3437) which suggested a substantial experience of social disadvantage. Only a small minority of the offenders were assigned to the latent group with the highest income (Trajectory 3: Highest income, 4.9%), with the mean annual income of €47,304 (SD: €16,711), exceeding the national average of the annual income of full-time workers (Statistics of Finland, 2019). Yet, even the trajectory with the highest

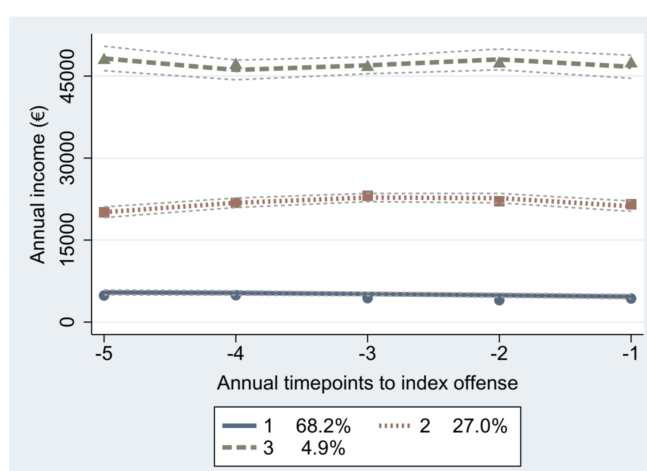

Fig. 3. Latent income trajectories of the offenders (N = 2233).

level of income did not display increasing income over time. Finally, roughly one-fourth of the offenders were assigned to the income trajectory between two extremities (Trajectory 2: Medium income, 27.0%) in which the annual income was €21,755 (SD: €6041). This trajectory rose slightly during the first years of the observation period, but ended up back at the starting level a year before the index offense. The individuals assigned to the lowest income trajectory were, on average, slightly younger, more often immigrants, more often females and had spent substantially more days in prison than offenders assigned to two other trajectories (Table S3).

As described in regards to violent trajectories, we re-estimated the latent income trajectories with the indicator of annual income being coded as missing for each individual at each measurement point in which the individual had stayed in prison more than half of the days (>182 days). In the analyses not reported here but available from the corresponding author, the slopes and the share of individuals assigned to each trajectory were almost exactly similar to the original model: Trajectory 1 (68.3%), Trajectory 2 (26.9%) and Trajectory 3 (4.8%). The results indicated that the incarceration was not a major factor driving the income trajectories.

The results of the chi-square test shown in Table 2 indicated that the latent income trajectory group was associated with the severity of the index offense ($\chi^2 = 145.52$, $p < .001$). For instance, more than four-fifths of the attempted and completed homicide offenders (82.3 and 85.5%, respectively) were assigned to the lowest income trajectory when the analogous share of the petty assault and assault offenders was 57.0 and 58.0%, respectively. Furthermore, 6.2 and 7.4% of the offenders of petty assault and assault, respectively, were assigned to the highest income trajectory, but only 3.1% of the aggravated assault offenders, 2.5% of completed homicide offenders, and 0.5% of the attempted homicide offenders were assigned to the same trajectory. In pairwise comparisons not shown here but available from the corresponding author, lethal offenders differed statistically significantly at the 0.05 level from offenders of less severe violence but not from aggravated assault ($\chi^2 = 4.22$, $p = .12$) or attempted homicide offenders ($\chi^2 = 4.11$, $p = .13$). Offenders of aggravated assault, differed statistically significantly only from petty assault ($\chi^2 = 65.91$, $p < .001$) and assault ($\chi^2 = 60.21$, $p < .001$) offenders. To summarize, the offenders committing more severe violence were, on average, more often assigned to the latent group with the lowest income. Yet, the association between latent income group and the severity of violent crime was not completely linear: more completed homicide offenders than attempted homicide offenders were assigned to the group of the highest income, and the offenders of petty assault had nearly similar group memberships as the offenders of assault.

5.2. Multilevel models of crime and income

In order to examine whether the seriousness of violent offense could be predicted based on preceding violent crime and income trajectories, we estimated two-level models separately for both outcomes. The model statistics are displayed in Table S6. Offenders of more severe violence displayed higher probabilities of criminal offending, and a steeper slope during the 9 years preceding the index offense than offenders of petty assault and assault (Fig. 4A). Yet, the confidence intervals of the offenders of aggravated assault, attempted homicide, and homicide were overlapping throughout the measurement period. Regarding annual income, the results suggested that offenders of more severe violence had substantially lower annual income (Fig. 4B). Offenders of attempted or completed homicide distinguished from offenders of petty assault, assault, and – contrary to the model estimating history of violent crimes – also from offenders of aggravated assault. As expected based on latent group models, the income levels of severe offenders were quite flat, or even descending for the offenders of attempted and completed homicide.[4,5]

Table 2
The associations between the index offense and income trajectory group (N = 2233).

	N	TRAJ 1	TRAJ 2	TRAJ 3	All
PA	609	57.0%	35.6%	7.4%	100.0%
A	609	58.0%	35.8%	6.2%	100.0%
AA	609	78.7%	18.2%	3.1%	100.0%
AH	203	82.8%	16.8%	0.5%	100.0%
CH	203	85.2%	12.3%	2.5%	100.0%

PA = Petty assault; A = Assault; AA = Aggravated assault; AH = Attempted homicide; CH = Completed homicide; $p < .001$; $\chi^2 = 145.518$.

6. Discussion

We estimated violent crime and income trajectories in order to examine the different pathways to violent offending. In particular, we wanted to study if the years preceding homicide are characterized by a downward spiral of increasing crime and socioeconomic disadvantage, and contrast such pathways to non-lethal forms of violence. Considering latent criminal trajectories, we found evidence of heterogeneous pathways to lethal violence. The latent trajectories were associated with the index offense: the more extensive violent history, the more severe the index offense. Yet, the *lethality* of the violent encounter among severe violent offenders could not be accurately predicted based on an individual's violent crime trajectory: roughly one-fifth of the completed homicide offenders (21.2%) and aggravated assault offenders (20.9%), and an even greater share of attempted homicide offenders (28.1%) were persistent violent offenders throughout the 9-year study period. Furthermore, for a large share of homicide offenders, the probability of violent arrest was low during the measurement period (<5%). The multilevel model examining the association of violent history and the index offense told a similar story: offenders of petty assault and assault displayed fewer violent tendencies of severe violence than other offenders, but the confidence intervals of offenders of aggravated assault, attempted homicide, and homicide were largely overlapping.

Considering latent income trajectories, most of the offenders had low annual income when the 5-year study period started, and their income did not alter in a substantial way during the follow-up period.

[4] As in regards to GBTM model, we re-estimated both two-level models and coded the indicators of violent offending and income as missing for the time periods of which the offenders were incarcerated at least half of the measurement period. As expected based on GBTM models, these restrictions did not alter the results. The results are available from the corresponding author.

[5] Since the distribution of income was skewed and included many zeros, we re-estimated the model while using the dichotomous indicator income as an outcome variable. First, we analyzed whether an offender had any annual income (1 = yes, 0 = no) and estimated the probabilities separately for each group of violent offenders. At the first measurement period, the confidence intervals of receiving any annual income were overlapping, but at the year before the index offense, the offenders of petty assault (0.81; 95% CI: 0.80-0.82) and assault (0.81; 95% CI: 0.81-0.82) had significantly greater probabilities of receiving any annual income than offenders of aggravated assault (0.72; 95% CI: 0.70-0.74), attempted homicide (0.60; 95% CI: 0.55-0.65), and completed homicide (0.68; 95% CI: 0.62-0.74). Second, we estimated whether offender's annual income was more than €10,000 (1 = yes, 0 = no). As could be expected, the offenders of less severe violence had significantly greater probabilities of obtaining the threshold than offenders of severe violence throughout the measurement period. Year before the index offense, the probabilities of earning more than €10,000 was the largest for offenders of petty assault (0.36; 95% CI: 0.35-0.37), second largest for offenders of assault (0.33; 95% CI: 0.33-0.34), third largest for offenders of aggravated assault (0.24; 95% CI: 0.24-0.25) whereas the confidence intervals of offenders of attempted homicide (0.14; 95% CI: 0.10-0.19) and completed homicide (0.14; 95% CI: 0.09-0.19) were largely overlapping. The results are available from the corresponding author.

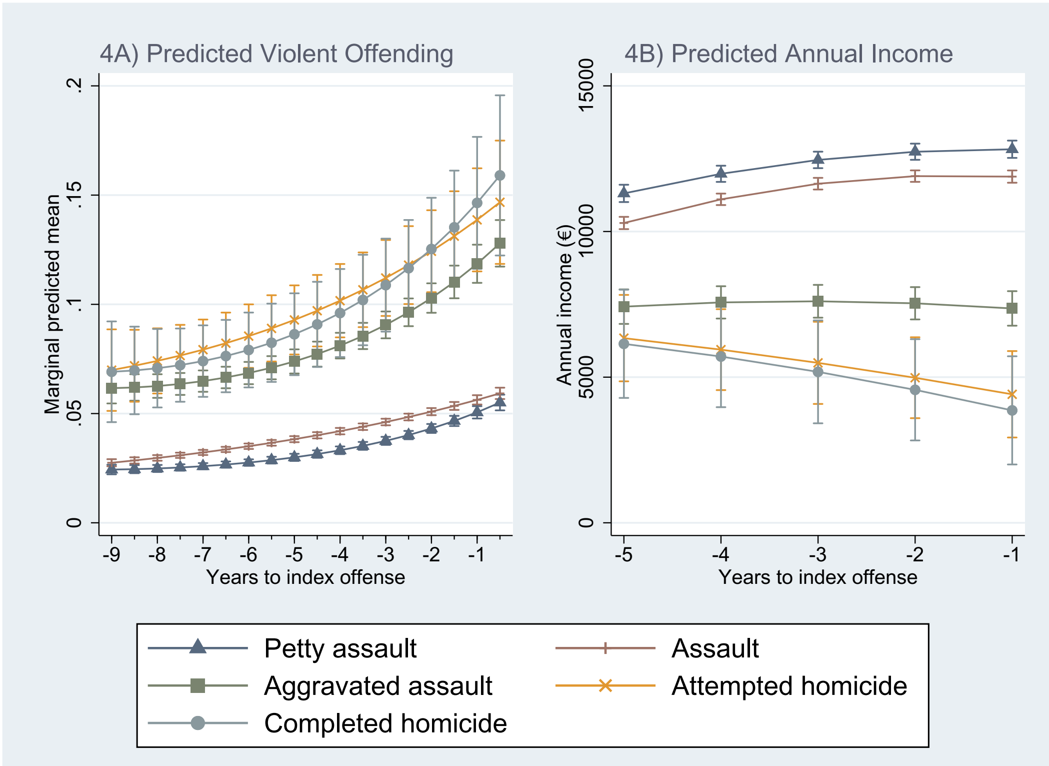

Fig. 4. Adjusted predictions of violent crime and income by offense type with 95% CIs (*N* = 26,303).

The differences between income trajectories were caused mostly by the differences in the intercept, not by the slopes of the trajectories, and income was associated with the severity of the index offense. The results from the multilevel model demonstrated that offenders of less severe violence had substantially higher annual income than offenders of aggravated assault, and – in particular – offenders of either attempted or completed homicide whose annual income was decreasing before the index offense. Yet, the decline in their income was rather small and the results indicated that offenders of severe violence experienced economic hardship years before the index offense. Thus, we find no evidence that a downward spiral of decreasing income would predict the lethality of the index offense.

Altogether, the results of the analyses suggest that the greatest divide in the violence severity continuum is between offenders of assaults and offenders of aggravated assaults, with the latter group largely resembling offenders of completed and attempted homicides. These offenders of severe violence also display a clear escalation in the frequency of violent offending. Given that "assault" is the largest category comprising offenses of varying severity, it is possible that a further disaggregation within this category might show a gradient-like association between offending severity and prior violent crime/income history. However, the key result of the analyses is that pathways of crime or social disadvantage to homicide do not appear qualitatively distinct from other serious violence, but rather represent an end of a continuum, where differences from other serious violent offenders are rather small. In this regard, our results are in contrast with the prior studies by Ganpat et al. (2014), DiCataldo and Everett (2008), and Dobash et al. (2007) by indicating that lethal offenders do not substantially differ from non-lethal offenders. Finally, the observed similarity of the pathways leading to homicide or other types of severe violence may reflect the randomness of lethal violence. Since the lethality of the violent encounter cannot be predicted based on an offender's history of violent crimes or income, future research would benefit from focusing on the social networks of the offenders (Green, Horel, & Papachristos, 2017) or the immediate situational factors and social interaction preceding the lethal incident (Ganpat, van der Leun, & Nieuwbeerta, 2017).

6.1. Limitations

This study is not without limitations. Since we relied on administrative data on violent behavior, our dataset includes only violent offenses that were reported to police. Comparative homicide research suggests that the clearance rate of Finnish homicides is exceptionally high (Liem et al., 2019). Yet, regarding less serious violence, it is certain that our data underestimates the prevalence of violent offenses. Furthermore, the same individuals could commit multiple violent offenses of differing severity during the sampling period years 2010–2011, and for clarity, we chose the first offense of each type of violent crime as the index offense. Hence, the results do not imply that offenders who committed petty assault, for instance, were somehow specialized in petty assaults, but the rationale here was to enable comparisons between violent offenses of differing severity. Since our dataset is based on police data instead of conviction data, some of the offenders might be exonerated, or the rubric might change in court. Nevertheless, we argue that police statistics are suitable data for the analysis of criminal behavior.

Regarding social disadvantage, we measured only one component of disadvantage: low annual income. Since the annual income of many offenders was extremely low throughout the measurement period, the analyses may suffer from a floor effect. Future research would benefit from incorporating multiple measures of strain and social disadvantage. Moreover, linear modeling may not be the best option for examining a continuous variable such as income since the distribution is skewed. However, our robustness tests with different thresholds of income largely supported the results of the main models (see footnote 5).

Finally, identifying latent groups was not completely unambiguous, and another researcher could identify a different number of groups by employing different fit criteria. Indeed, in his simulation experiment, Skardhamar (2010) demonstrated that GBTM is not a reliable method for testing the existence of distinct latent groups; in the presence of unobserved heterogeneity, the method will always identify groups and the model diagnostics are not reliable indicators of the "distinctness" of these groups. Thus, the latent groups emerging from the dataset should not be interpreted as "real" groups or evidence of taxonomic theories, but as one way of summarizing the data. However, our main interest lies in the association of the index offense and the latent group membership, and regardless of the number of latent groups, our results suggest that based on prior violent crime and income, it is not possible to predict whether an individual will commit serious non-lethal or lethal violence.

7. Conclusions

Interpersonal violence is a serious problem with detrimental consequences to societies and individuals. Our results indicate that interventions for reducing homicide mortality should be targeted for the whole group of offenders of severe violence since lethal offenders do not differ from offenders who commit attempted homicide, or aggravated assault. This finding is especially relevant in Finland, which has a long history of having higher homicide rates than its Western counterparts. Moreover, the empirical evidence on similarity of lethal and non-lethal offenders is relevant for criminal theories explaining causes of interpersonal violence.

As mentioned earlier, homicide research has developed somewhat separately from general criminal career research, which may have hampered seeing the commonalities between homicide and other types of violence. Based on the results of the current study, etiological research on homicide might benefit from boosting the samples with other serious violence. Given the fortunate rarity of homicide in Western societies, research on determinants of violence could combine samples of homicide offenders with additional samples of other serious violent offenders. Such research could provide more insight into the (in)distinctiveness of homicide, as well as provide more accurate estimates of general determinants of violence. Such larger datasets would be particularly valuable for more robust within-individual designs that examine the impact of time-varying factors on violent offending. Existing Finnish studies suggest that common time-varying factors such as employment or experiencing economic hardship are not very useful in predicting violence (in contrast to property crime), and violence prevention would benefit from discoveries of dynamic factors that are associated with higher within-individual risk of violence.

Funding

This study received funding from the Academy of Finland (grant number 316595).

Appendix A. Descriptive statistics of the full and the matched sample.

	Petty assault	Assault[a]	Aggravated assault[a]	Attempted homicide	Completed homicide
Full sample (*N* = 26,303)					
N	7970	15,817	1995	318	203
Male (%)	78.96	84.26	83.66	83.65	88.67
Immigrant (%)	12.41	13.03	11.23	8.81	7.88
Mean age (SD)[b]	34.49 (13.60)	32.54 (12.73)	32.73 (12.25)	35.78 (12.49)	37.40 (13.01)
Annual days in prison, mean (SD)[c]	3.60 (17.88)	5.05 (22.57)	14.86 (39.34)	18.50 (40.25)	25.24 (56.36)
Matched sample (*N* = 2233)					
N	609	609	609	203	203
Male (%)	88.67	88.67	88.67	88.67	88.67
Immigrant (%)	7.88	7.88	7.88	7.88	7.88
Mean age (SD)[b]	37.40 (12.98)	37.40 (12.99)	37.40 (13.00)	37.39 (13.01)	37.40 (13.01)
Annual days in prison, mean (SD)[c]	5.31 (22.32)	5.80 (22.89)	17.06 (41.04)	21.16 (44.28)	25.24 (56.36)

[a] Including attempts.
[b] Measured at the time of the index offense.
[c] 9-year observation period.

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jcrimjus.2020.101685.

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